Energy Saving Potentials of Connected and Automated Vehicles

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Abstract

Connected and automated vehicles (CAV) are marketed for their increased safety, driving comfort, and time saving potential. With much easier access to information, increased processing power, and precision control, they also offer unprecedented opportunities for energy efficient driving. This paper is an attempt to highlight the energy saving potential of connected and automated vehicles based on first principles of motion, optimal control theory, and a review of the vast but scattered eco-driving literature. We explain that connectivity to other vehicles and infrastructure allows better anticipation of upcoming events, such as hills, curves, slow traffic, state of traffic signals, and movement of neighboring vehicles. Automation allows vehicles to adjust their motion more precisely in anticipation of upcoming events, and save energy. Opportunities for cooperative driving could further increase energy efficiency of a group of vehicles by allowing them to move in a coordinated manner. Energy efficient motion of connected and automated vehicles could have a harmonizing effect on mixed traffic, leading to additional energy savings for neighboring vehicles.

Keywords: connected vehicles, automated vehicles, eco-driving, optimal control, anticipative driving, collaborative driving.

1. INTRODUCTION

The shift that we are witnessing toward vehicle connectivity and autonomy is going to be perhaps, the most disruptive since the early days of automobiles and could revolutionize movement of people and goods. According to IHS Automotive, the number of connected cars sold globally will grow more to 152 million across the globe by 2020, a six fold increase with respect to 2015 (McCarthy, 2015). Another estimate puts the number of connected vehicles at 250 million vehicles by 2020 (Gartner, 2015), a fourth of the billion cars that are in service today. In 2016 the US Department of Transportation issued a notice of proposed rule making, that if implemented would require Vehicle-to-Vehicle (V2V) connectivity on all new light-duty vehicles and is intended to reduce the number of car accidents (NHTSA, 2016b). Similar provisions and guidelines are envisioned for Vehicle-to-Infrastructure (V2I) communication (FHWA, 2015). With implementation of such mandates the number of connected cars with access to information and data will rapidly increase. On a different front, major auto manufacturers, technology firms, and startup companies have started a race toward building fully automated cars. Many automated functions such as adaptive cruise control and lane keeping assist are already available on several production vehicles. It is expected that first fully automated vehicles be available for sale before 2020 (Center for Sustainable Systems, 2016; Alexander-Kearns et al., 2016). A projection is that 20-40% of vehicle sales be automated by 2030 and full penetration could happen in several stages over the next few decades (Litman, 2017).

This level of connectivity and autonomy will transform transportation of people and goods in several dimensions with important societal and economical impacts: improved safety, increased comfort, time saving potential, and more efficient road utilization are among the most widely discussed positive impacts of CAVs. Fully automated vehicles could improve mobility of young, elderly, and people with disability who are unable to drive today. Ride sharing and

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on-demand mobility services could gain more popularity due to reduced labor cost, influencing also urban planning and land use.

Energy use has not been the core consideration in development of connected and automated vehicles, but it could be impacted significantly. The impact could be positive or negative according to (Brown et al., 2014; Wadud et al., 2016) which is summarized in Table 1. A careful scenario analysis in (Wadud et al., 2016) shows vehicle automation could reduce energy use and green house gas emissions in half in an optimistic scenario or double them in a "dystopian nightmare", depending on the effects that come to dominate. Increased opportunities for eco-driving and platooning, traffic harmonization, vehicle light-weighting enabled by lower crash risk, vehicle right-sizing for number of travelers, de-emphasized vehicle performance, car-sharing and on-demand mobility, and reduced infrastructure footprint of automated vehicles all contribute to improved energy utilization according to (Wadud et al., 2016). But according to the same study, the increase in vehicle miles traveled due to lower travel costs, addition of new user groups (young, elderly, disabled), higher highway speeds, and increased vehicle features can also dramatically increase the energy footprint of vehicle automation. The outcomes depend on which scenarios prevail and proactive policy making is essential to steer the technology toward energy efficiency as also emphasized in (Wadud et al., 2016; Simon et al., 2015; Alexander-Kearns et al., 2016). The authors of (Greenblatt and Shaheen, 2015) speculate that the aggregate energy and environmental impact of automated and on-demand mobility could be positive; but acknowledge a big shift from historical trends that needs to be carefully watched by policy makers and planners.

Table 1: Potential Impact of CAVs on a) energy intensity or user intensity according to (Brown et al., 2014) b) operational energy use by year 2050 according to (Wadud et al., 2016).

Contributing Factors	(Brown et al., 2014)	(Wadud et al., 2016)
platooning	(-)10 % EI*	(-) 2-10 %
eco-driving	(-)15-40 % EI	(-) 20 %
eco-routing	(-) 5 % EI	NA
congestion mitigation	NA	(-)2-4%
de-emphasized performance	NA	(-) 5-23 %
vehicle light-weighting	(-) 50 % EI	(-) 5-23 %
vehicle right-sizing	(-) 12† % UI**	(-) 20-45 %
changed mobility services	NA	(-) 0-20 %
infrastructure footprint	NA	(-) 2-5%
reduced parking search	(-) 4 % UI	NA
enabling electrification	(-) 75 % FI***	NA
higher highway speeds	(+) 30 %	(+) 5-25 %
increased features	NA	(+) 0-10 %
travel cost reduction	(+) 50 % UI	(+) 5-60 %
new user groups	(+) 40 % UI	(+) 2-10 %

*EI: Energy Intensity **UI: User Intensity ***FI: Fuel Intensity † higher occupancy facilitated by IT and automated carpooling

This paper takes a more in-depth look at increased opportunities for energy efficient driving with connected and automated vehicles, disregarding second order effects of connectivity and automation, such as increased vehicle miles traveled or reduced vehicle weight. By connected we are referring to vehicles that use communication technologies such as DSRC, cellular, or even Wi-Fi for vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-cloud (V2C) communication. The U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA) defines fully automated vehicles as those in which operation of the vehicle occurs without direct driver input to control the steering, acceleration, and braking and are designed so that the driver is not expected to constantly monitor the roadway while operating in self-driving mode (USDOT, 2013). In categorizing partial automation, NHTSA's federal automated vehicles policy (NHTSA, 2016a) adopts that of Society of Automative Engineers (SAE) definitions for levels of vehicle automation. Automation levels range from no automation with full driver control (Level 0) to full automation with no driver control (Level 5). Many of the benefits discussed in this paper are realizable with partial level 2 or 3 automation as they mostly rely on automated speed and steering control which can be overseen and overridden by a human driver.

Because CAVs are capable of sensing more accurately, processing more information, and can be more tightly controlled, they benefit more from information offered by connectivity and road preview. With higher penetration rate of CAVs, opportunities increase for vehicle to vehicle communication and cooperative control; which can lead to additional energy efficiency gains. Despite these prospects, connected and automated vehicle research and development have been mostly on software, sensing, and safety and there are limited results on energy efficiency potentials.

Over the past decade, various research groups have shown the positive influence of telematics, road preview, and connectivity on energy efficiency of conventional and hybrid vehicles through simulation and experimental investigations. For instance, in (Manzie et al., 2007) it is shown that as little as 7 seconds traffic look-ahead capability could have the same energy efficiency benefit as hybridization. Due to the complex nature of the problem (different vehicle configurations, variability of scenarios, and sensitivity to choice of algorithms) the reported values for energy efficiency benefits are scattered and a concerted effort is needed to summarize the findings and put them in context. Such a summary not only helps researchers in the field but can inform policy making in regulatory units.

We start by discussing the fundamentals of energy efficient driving based on a first principle energy analysis in Section 2. Our reference to eco-driving implies economic and not ecologic driving as they are not necessarily the same; lowering energy use is not equivalent to lowering emissions (Mensing et al., 2014). As formalized in (Sciarretta et al., 2015) and (Saerens, 2012) many eco-driving problems are optimal control problems; but to keep the paper readable to a more general audience we limit use of theory of optimal control to an appendix. The flow of the rest of the paper is shaped by the authors' past research on eco-driving and backed by the many papers that have emerged on the topic, mostly over the past decade. This is by no means a comprehensive review of existing literature as a wide range of publications exists. In particular we do not consider the topic of eco-routing and dynamic route guidance that have been discussed in several recent publications, for instance in (Boriboonsomsin and Barth, 2009; Boriboonsomsin et al., 2012; Kubička et al., 2016; De Nunzio et al., 2016). Nor we discuss opportunities for better traffic response signal control, ramp metering, and other infrastructure based controls that could also enhance energy efficiency.

In Section 3 the importance of anticipation for efficient driving is explained. In particular we discuss opportunities that arise for individual CAVs by anticipating future road slope and geometry, macroscopic state of traffic, color of upcoming traffic signals, and microscopic motion of their neighboring vehicles. This allows CAVs to more judiciously choose their velocity and lane to minimize wasteful braking and idling and also enables predictive powertrain control due to increased certainty about future vehicle motion. With increased penetration of CAVs, more opportunities arise for collaborative driving which could further enhance energy efficiency as discussed in Section 4. In particular we discuss platooning, cooperative adaptive cruise control, cooperative lane change and merge, and cooperative intersection control for a CAV fleet. The impact on mixed traffic is discussed briefly in Section 4.4, followed by conclusions in Section 5.

2. Fundamentals of Energy Efficient Driving

Energy used by a vehicle depends very much on the way its driven. There is a large body of scientific literature on energy efficient- or eco- driving (Monastyrsky and Golownykh, 1993), (Sciarretta et al., 2015), practical guides on hypermiling (Hickman, 2011), and the potential impact on energy use and carbon emissions (Barkenbus, 2010). Connected and automated vehicles have the potential to excel at efficient driving because of their increased situational awareness and ability to execute more complex maneuvers more precisely. Before discussing specific scenarios where CAVs can save energy, here we take a closer look at fundamentals of energy efficient driving. We will consider only a vehicle's longitudinal motion governed by Newton's second law of motion and disregard the constraints imposed by the motion of surrounding vehicles:

$$m\frac{dv}{dt} = F_w - mg(sin\theta + C_{rr}cos\theta) - \frac{1}{2}\rho_a A C_D v^2 \tag{1}$$

where m is mass of the vehicle, including powertrain inertial effects, v is forward velocity. Here F_w is chosen to be the sum of tractive or braking force at the wheels, thus decoupling the role of vehicle powertrain in the initial part of this discussion. In the term representing road loads, C_{rr} is the coefficient of rolling resistance and θ is the road slope. In the term representing aerodynamic drag, ρ_a is air density, A is vehicle front area, C_D is aerodynamic drag coefficient.

The instantaneous power needed at the wheel is $F_w(t)v(t)$. Therefore, the net energy needed at the wheel, E_w, to cover a distance s_f in t_f unit of time can then be calculated as:

$$E_w = \int_0^{t_f} F_w(t)v(t)dt = \int_0^{s_f} F_w(t(s))ds = \\ \int_0^{s_f} \left(m\frac{dv}{dt} + mg(sin\theta + C_{rr}cos\theta) + \frac{1}{2}\rho_a A C_D v^2 \right) ds \tag{2}$$

With the reasonable assumption that m, g, C_{rr}, ρ_a, and A are constants during a trip, integration yields:

$$E_w = \frac{1}{2}m(v_f^2 - v_0^2) + mg\Delta h + mgC_{rr}\Delta x + \frac{1}{2}\rho_a A \int_0^{s_f} C_D(s)v^2(s)ds \tag{3}$$

where v_0 and v_f are velocities at origin and destination respectively, Δh is total elevation change during the trip, and Δx is the horizontal distance covered. Here we assume the drag coefficient can vary along the road, due to potential for platooning or drafting which could reduce aerodynamic drag.

The first and the second terms in Equation (3) represent the change in kinetic and potential energy respectively and are dictated by initial and terminal conditions, so they do not offer opportunities for reducing E_w. Note that road grade does not appear after integration; however we will explain later that because of constraints on velocity and powertrain output, the elevation profile along a trip can have a significant effect on energy use and prior knowledge of it can help save fuel via better constraint management. The term $mgC_{rr}\Delta x$ represents the irreversible frictional loss and is a function of (horizontal) trip distance and C_{rr}. So if there is a choice, one must choose shorter routes with lower C_{rr} (concrete road over sand road) to save energy. With connectivity there may be opportunities to evaluate this term more accurately. The last term, the energy lost to aerodynamic drag, is the only term that can be influenced by the decisions along the route and therefore should be a core consideration in eco-driving. The energy needed at the wheel can be reduced by joining a tight platoon thus lowering C_D. The vehicle velocity plays an important role and obviously lower speeds result in lower losses to drag. More specifically when C_D is constant the drag term can be easily reorganized as follows (Kubička et al., 2016):

$$\frac{1}{2}\rho_a A \int_0^{s_f} C_D(s)v^2(s)ds = \frac{1}{2}\rho_a A C_D(\bar{v}^2 + \sigma_v^2)s_f \tag{4}$$

where $\bar{v} = \frac{\int_0^{sf} v(s)ds}{s_f}$ is the average velocity over position and $\sigma_v^2 = \frac{\int_0^{sf} (v(s)-\bar{v})^2 ds}{s_f}$ is its variance. Therefore to minimize drag losses it is best to drive with a low and constant ($\sigma_v^2 = 0$) speed. Note also that at constant speed, the drag loss is proportional to s_f^3, therefore taking a road that is 10% shorter, reduces drag losses by 27% which can be significant at high speeds.

When the initial and final velocity are different, the velocity cannot be constant. Our optimal control analysis presented in the Appendix, indicates that in such a situation, it is best to accelerate (or decelerate) as quickly as possible to a constant low speed and then decelerate (or accelerate) quickly to the final desired speed (bang-singular-bang solution). Note that we postpone the discussion of velocity and position constraints to Sections 3.1 and 3.3 respectively.

Depending on initial and final conditions, the required energy at wheel E_w could be negative. Moreover $\frac{d}{ds}E_w$ which is equal to the required wheel force F_w, can be negative: for instance when decelerating to a stop ($\frac{dv}{dt} < 0$) or on downhill slopes ($\theta < 0$) as inferred from Equation (1). When $F_w < 0$, it is necessary to apply the brakes or rely on engine braking, thus wasting energy as heat. Even in hybrid and electric vehicles with recuperative brakes, a part of available braking energy is lost as heat. Therefore for eco-driving it is best to minimize situations in which $F_w < 0$, in particular braking should be avoided when possible. This means that when deciding to slow down or to stop, it is best to coast with the engine disengaged ($F_w \approx 0$) and rely on rolling resistance and aerodynamic drag to slow the vehicle down. We note that coasting will increase the stopping distance which may not be always safe or desirable. Therefore anticipation of slow downs in advance, provides more time and opportunity for gradually reducing the speed. Vehicle connectivity could enable anticipative driving as discussed in more detail in Section 3. We also note that pure coasting may not be always energy optimal, for instance when traveling between two stops in a fixed time, the best final decelerating strategy is a combination of coasting and maximal braking as explained in the Appendix.

This is classic problem that has been addressed in optimal control of trains that have to travel between two stations in a fixed amount of time (Asnis et al., 1985; Howlett, 2000).

When descending down a steep road and in a hypothetical scenario when there are no upper bounds on velocity, it is more energy efficient to coast down the hill ($F_w \approx 0$) allowing the velocity to increase toward the equilibrium imposed by rolling resistance and aerodynamic drag. Unfortunately this is very unsafe and often impractical due to road speed limits and the bounds imposed by preceding vehicles. However if the road profile is known in advance, the vehicle can start coasting early in anticipation of an imminent descent, allowing it to utilize the limited velocity band more effectively. An automated vehicle can execute such a maneuver more precisely than a human driven vehicle as explained in more detail in Section 3.1.

The above discussion was focused on increasing "wheel-to-distance" (Sciarretta et al., 2015) energy efficiency and did not address "tank-to-wheel" energy efficiency which is powertrain dependent. The two problems are not entirely decoupled: for instance we showed that low constant velocities improve "wheel-to-distance" energy efficiency due to lower drag. A gasoline engine on the other hand is not most efficient at low loads seen at low speeds. The engine sweet spot is typically at relatively large engine loads. To strike a balance (running the engine efficiently and maintaining a low average speed), the engine could be periodically turned on at high load and then turn off; in a "pulse-and-glide" strategy as shown schematically in Figure 1. The effectiveness of pulse and glide algorithms is shown analytically in (Gilbert, 1976), using theory of optimal control in (Sciarretta and Guzzella, 2005; Li and Peng, 2011), and experimentally in (Lee, 2009) but overall the existing literature presents mixed and sometimes conflicting results. We note that pulse and glide may not be a practical eco-driving strategy because velocity variations are uncomfortable to passengers and disruptive to traffic. Also according to (Lee, 2009) pulse and glide may not be an effective approach in vehicles with automatic transmission due to torque converter losses.

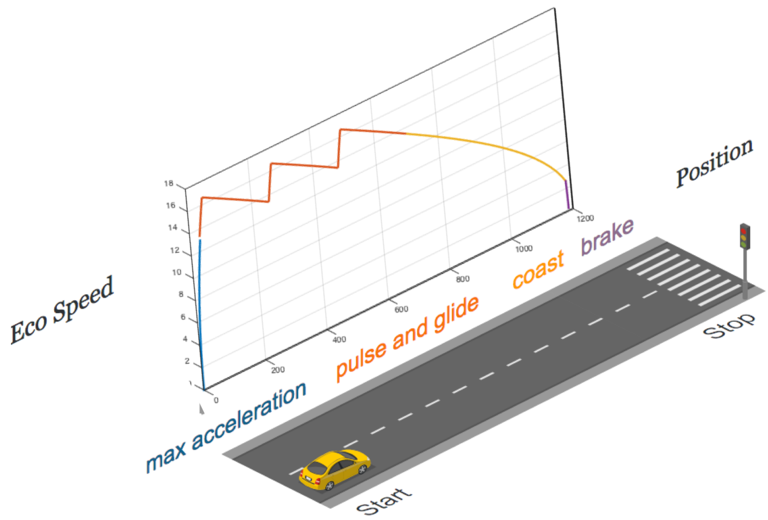

Figure 1: Eco driving between two stopping points. The combustion engine car starts with maximum acceleration, pulse-and-glides around its cruise speed, followed by coast down and final maximal braking to a stop. Parts of the image were created on `https://icograms.com`.

In hybrid vehicles, the battery energy storage buffer allows to (partially) decouple the engine load/speed from the wheel load/speed. Therefore the engine can be run more often near its sweet spot, even at low road loads and speeds. Moreover, regenerative brakes contribute to higher energy efficiency. Nevertheless, because the electromechanical energy conversion is always lossy, eco-driving practices can be beneficial even for hybrid vehicles. For instance using connectivity and road preview allows predictive utilization of the limited battery energy buffer to save energy (Zhang et al., 2010). A pulse and glide strategy can save fuel in hybrids as well (Lee, 2009) but may be undesirable.

The electric motor in electric vehicles is more efficient at lower torques and therefore the energy-optimal operation strategy, unlike for gasoline vehicles, is not pulse and glide (Sciarretta et al., 2015; Han et al., 2018). Analytical solutions based on optimal control theory show that the optimal speed profile for an electric vehicle is a parabolic function of time, quite different from that of gasoline engine vehicles (Han et al., 2018). Here automated driving may provide an advantage in the ability to adhere to more complex speed profiles for energy saving.

3. Anticipation in Connected and Automated Driving

CAVs offer huge potentials for boosting road safety, capacity, and efficiency, because of their ability to process data from many more sources (e.g. V2X fused with on-board sensing) and their ability for more precise positioning and control than human drivers. While similar information can be processed, and provided to connected human-driven vehicles (Barth and Boriboonsomsin, 2009) (Stahl et al., 2016) (e.g. as optimal speed/lane advisories), only fully automated vehicles can be made to comply with and reliably follow real-time energy-efficient commands. Even in mixed-traffic that involves other non-automated vehicles, energy-efficient automated vehicles can have a positive impact on the energy efficiency of surrounding traffic as will be illustrated later. Automated cars have the potential to uncover the "driving signature" of their neighboring vehicles and predict their most likely actions. They can also anticipate probable locations of slow-downs by systematic evaluation of historical data. Connectivity between cars and infrastructure can make much more information available to each vehicle and the vehicles can form groups and act cooperatively. All of these advances, when put into an organized framework, can help better anticipation and enable improved traffic flow, increased safety, and reduced energy consumption.

3.1. Anticipating State of the Road

Prior knowledge of road speed limits, safe speeds on curved roads, and an estimate of average traffic speed allows for more energy efficient velocity transitions in anticipation of the change in velocity constraints. Speed limit is a standard feature on modern onboard navigation units. Road curvature may be extracted from navigation maps to calculate the likely (safe) speed on a curve. Curve speeds can also be crowdsourced from connected vehicle data. Average traffic speeds for upcoming segments of a trip can be queried from a Traffic Management Center (TMC) that operate based on local sensors and cameras or estimated from traffic feeds that mostly rely on crowdsourced information, such as feeds of Google, Here, Waze, and Inrix as of 2017. Dynamic spatiotemporal evolution of traffic speed can be estimated via a faster-than-real-time traffic simulation model which is initialized by current traffic speed, deterministically (Asadi et al., 2010) or probabilistically (Wan et al., 2014). In absence of real-time traffic information services, time- and location-specific historical traffic data can be used as a baseline predictor (Wan et al., 2018). Traffic speed can be imposed as a spatio-temporally varying upper bound on the CAV speed (Asadi et al., 2010). Speed limit, curve and traffic speeds can be unified (Schepmann and Vahidi, 2011) into a single spatiotemporal bound on CAV velocity and used not only to optimize velocity transitions of a CAV but also inform its predictive powertrain control functions.

Another dominating factor in vehicle power demand is road grade, in particular on steep roads, and more so for heavier vehicles. While road grade does not explicitly impact E_w as shown in Equation (3), it influences velocity and torque constraints and gear selection. Therefore advanced knowledge of the road grade, obtained from 3D road maps, is very beneficial in predictive powertrain control as shown for instance in (Back et al., 2004; Zhang et al., 2010). Additionally, due to constraints on velocity, prior knowledge of road grade will allow more judicious use of available velocity band and gear selection (Terwen et al., 2004; Fröberg et al., 2006; Huang et al., 2008; Hellström et al., 2009, 2010; Kamal et al., 2011; Lu et al., 2017); for instance a vehicle can slow down in anticipation of a steep descent or speed up in preparation for a climb. The optimal solution can be non-trivial as shown for a heavy duty vehicle in (He et al., 2016). Daimler already has a predictive cruise control function in production that adjust a heavy duty truck speed (Freightliner, 2009) and gear (Barry, 2012) in anticipation of upcoming road grade to increase its energy efficiency by 3% on a highway. This level of achievable improvement is consistent with results in literature as summarized in Table 2. Predicted velocity transitions and road grade can reduce energy use also via predictive power split in hybrid powertrains (Sun et al., 2015), fuel cut-off (Dornieden et al., 2012) and cylinder deactivation (Sujan et al., 2014) in combustion engines, and thermal load management (Braun et al., 2010). While such predictive powertrain control functions can be exercised in conventionally driven vehicles and some have been extensively studied, they will have a larger impact in CAVs. Real-time access to information due to connectivity and absence of a human driver in a CAV increases certainty of predictions and therefore effectiveness of predictive powertrain control as depicted schematically in Figure 2.

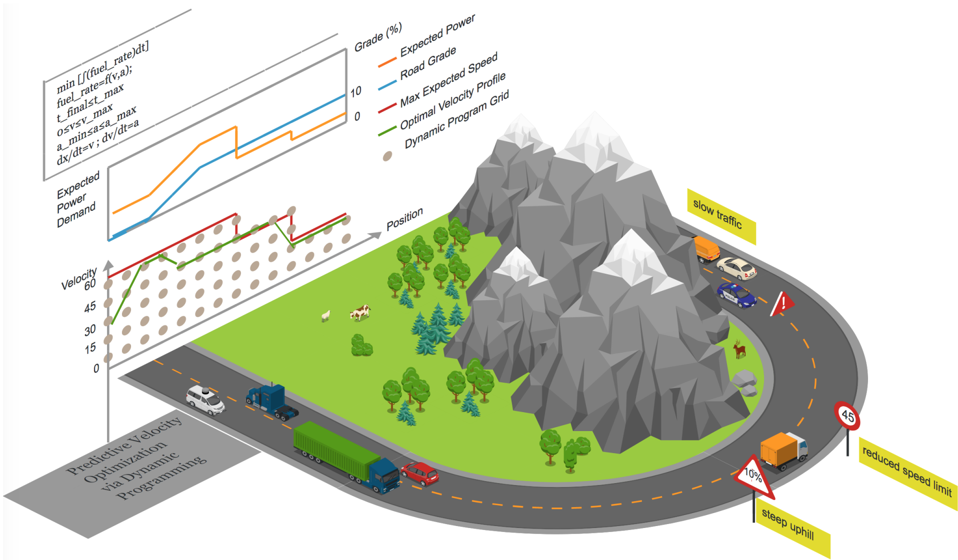

Figure 2: Eco driving in anticipation of upcoming hills, changes in speed limit, and slow traffic. The white CAV solves a dynamic program to find the fuel optimal velocity trajectory given road power demand and constraints. The image was created on `https://icograms.com`.

Table 2: Summary of selected published results on energy efficiency gain enabled by road grade preview.

Ref.	Methods and Conditions	Efficiency gain (%)
(Huang et al., 2008)	S†, 32 ton class 8 truck constrained NLP, preview horizon: 1500m optimized velocity, gear, and throttle input route 1: $-3.7° \leqslant \theta \leqslant +4.7°$, $\mu_\theta = 0.29°$, $\sigma_\theta = 1.32°$ route 2: $-4.3° \leqslant \theta \leqslant +3.0°$, $\mu_\theta = -0.21°$, $\sigma_\theta = 1.06°$	 +2.6 +2.0
(Hellström et al., 2009) (Hellström et al., 2010)	E†† 39 ton SCANIA truck 120km highway, Södertälje to Norrköping, Sweden dynamic programming, preview horizon: 1500m optimized velocity; gear was preselected	+3.5
(He et al., 2016)	S, 29 ton class 8 Navistar truck 4 km single valley profile $h(s) = 30(1 - s/2000)^2$ Pontryagin Min. Principle & numerical continuation horizon=4000 m, optimized velocity and gear	+11.6 over a single valley
(Kamal et al., 2011)	S, 1.3 Liter gasoline engine passenger car Simplified polynomial fuel consumption model Model predictive control, optimized velocity 2.5km Yuniba Dori Road, Fukuka City, Japan $-5.0° \leqslant \theta \leqslant +6.0°$	+4-7
(Zhang et al., 2010)	S, 2000 kg hybrid electric vehicle dynamic programming, preview horizon: full trip constant speed, optimized power split 36 and 48 km hilly roads, Contra Costa, California PSAT (ANL) fuel economy evaluation route 1 $-4.3° \leqslant \theta \leqslant +3.0°$, $\mu_\theta = -0.21°$, $\sigma_\theta = 1.04°$ route 2: $-8.0° \leqslant \theta \leqslant +5.3°$, $\mu_\theta = -0.17°$, $\sigma_\theta = 2.3°$	 +0-3.0 +0-6.0

†S: Simulation ††E: Experimental

3.2. *Anticipating Signal Phase and Timing*

When driving on arterial roads, repetitive stops at traffic signals result in loss of energy due to braking and idling, engine and brake wear, and can be uncomfortable and frustrating for passengers. Some of these stops are unnecessary, in particular under light to medium traffic conditions, and are due to lack of information about the state of traffic lights. In an ideal connected urban area with Vehicle-to-Infrastructure (V2I) connectivity, Signal Phase and Timing (SPaT) can be broadcast to approaching vehicles; so that connected vehicles adjust their speed for a timely arrival at a green light as shown schematically in Figure 6. Vehicle autonomy further facilitates this scenario by taking the burden of speed adjustments away from human drivers.

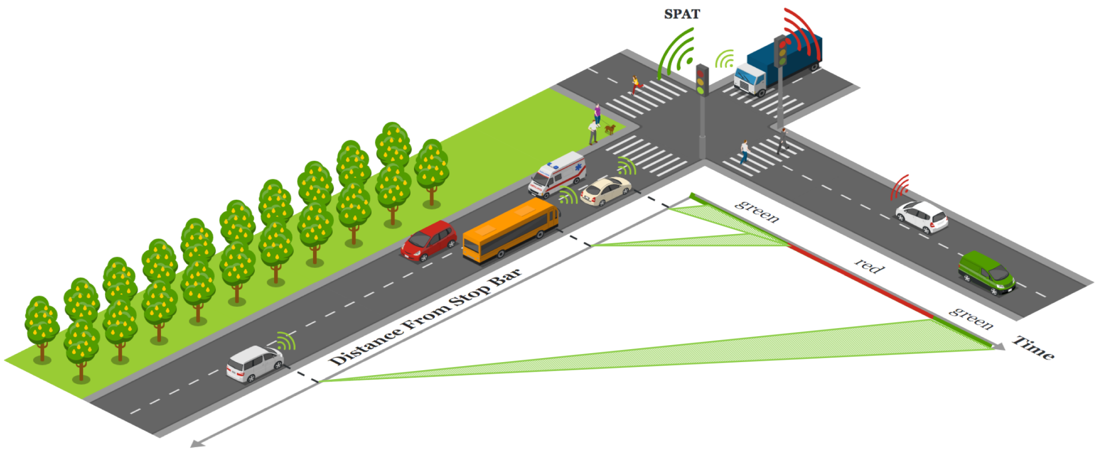

Figure 3: Schematic of eco-driving with SPAT preview. Shaded triangles contain feasible paths to green intervals of the traffic light for the 3 vehicles moving from bottom left to top right. Most parts of the image were created on `https://icograms.com`.

Eco-driving at signalized intersections and its impact on energy efficiency has been the topic of many papers in recent years. One of the earlier works was presented in (Asadi and Vahidi, 2009) and expanded in (Asadi and Vahidi, 2011) and showed potential for significant fuel savings in a simulation study. These positive results have been corroborated in (Mandava et al., 2009; Rakha and Kamalanathsharma, 2011; Mahler and Vahidi, 2014) and many more publications that have followed them. Experimental results in isolated environments (Xia et al., 2012; Jin et al., 2016) and in real-world traffic conditions (Mahler, 2013; Hao et al., 2017; Mahler et al., 2017) show that considerable fuel saving (5-15%) is possible with human drivers in the loop. Even more energy saving is expected in automated driving (or with automated cruise control) where vehicles can adjust their speeds more precisely and effortlessly.

The technology for transmitting traffic signal information to subscribing vehicles has been demonstrated in several research projects (Koukoumidis et al., 2011), (Xia et al., 2012) and (Mahler et al., 2017). The SPaT information may be directly transmitted to vehicles within range using Dedicated Short Range Communications (DSRC) technology (Hao et al., 2017) or may become available by the traffic control center via cellular networks as shown in (Mahler et al., 2017). A software architecture for cellular communication of SPaT from a server to subscribing connected vehicles is described in (Mahler et al., 2017). Alternative means of inferring SPaT information via on-board cameras (Koukoumidis et al., 2011) and via crowd-sourcing (Fayazi et al., 2015; Fayazi and Vahidi, 2016) have also been proposed. Connected Signals (ConnectedSignals) is a company in Oregon, USA that has been attempting to build a SPaT information repository one city at a time and provides speed advisory to human drivers via a mobile app (Marshall, 2016). However a much needed real-time server that covers large urban areas is still missing. In absence of real-time SPaT information, it is still possible to use history of observation during daily commutes and to estimate the probability of a green or red over a future horizon, conditioned on the current color of the light (Mahler and Vahidi, 2014). Even when SPaT is available in real-time; the future color of the light is not known with certainty, for instance when the light is actuated by the state of loop detectors. In such a scenario one can still use historical trends, to predict the probability of a red or green over a future time horizon (Bodenheimer et al., 2014).

While simple logical rules, such as those in (Asadi and Vahidi, 2009), can be effectively used when approaching a single traffic signal, optimizing the trajectory for a sequence of traffic lights can benefit from more formal methods. The velocity planning problem can be formulated as an optimal control problem where the goal could be minimizing or reducing energy consumption subject to the constraint imposed by red signals. Analytical solution, obtained using Pontryagin Minimum Principle, indicate that fuel optimal solution for a conventional vehicle[1] is not intuitive and

[1]The solution for hybrid and electric cars (Dib et al., 2014) is different and could be more complex.

Table 3: Summary of selected published results on energy efficiency gain enabled by SPaT anticipation with respect to conventional vehicles without SPaT information.

Ref.	Methods and Conditions	Efficiency gain[*] (%)
(Asadi and Vahidi, 2009) (Asadi and Vahidi, 2011)	S[†], lone vehicle, 10 fixed time lights real SPaT: Greenville, SC timing cards 1.7 L 4-cylinder gasoline engine, high fidelity vehicle model in PSAT (ANL)	+24-29
(Mandava et al., 2009)	S, 10 fixed time lights, stochastic parameter variation passenger car and SUV, CMEM models (Scora and Barth, 2006)	+12-14
(Kamalanathsharma and Rakha, 2013)	S, 1 fixed time light varying road conditions, random initialization Virginia Tech fuel consumption model (Rakha et al., 2011)	+20
(Mahler and Vahidi, 2014)	S, 3 fixed and variable timing lights probabilistic SPaT, probabilistic planning Monte Carlo Evaluation (3000 scenarios)	+16
(Xia et al., 2012)	E[††], no traffic 1 fixed time signal, 4G cellular comm. 2011 BMW 535i	+13
(Mahler, 2013) (Mahler et al., 2017)	E, real city traffic, real-time TMC data, 4G cellular comm. Mix of 10 fixed time and actuated signals 2011 BMW 535i, 4 complying drivers	+9
(Hao et al., 2017)	E, real city traffic coordinated actuated signals, DSRC comm. 2008 Nissan Altima, 2 complying drivers	+2-6
(Koukoumidis et al., 2011)	E, real city traffic 2 fixed time lights camera SPaT estimation- V2V comm. 2001 2.4L PT Cruiser, 1 complying driver	+25
(Wan et al., 2016)	S, network wide effect 4 fixed time signals, multi lane Paramics (Paramics, 2009) microsimulations, mixed traffic 50% CAVpenetration, 900 veh/hour/lane polynomial fuel consumption model	+25 (CAV) +6 (surronding traffic)
(Xia et al., 2013)	S, network wide effect 11 fixed time signals, one lane Paramics microsimulations, mixed traffic 50% CAVpenetration, 300 veh/hour/lane CMEM (Scora and Barth, 2006) fuel consumption model	+12.5 (CAV) +7.5 (all traffic)
(Kamalanathsharma et al., 2015)	S, network wide effect 1 fixed time signals, single lane at grade INTEGRATION microsimulation package varied CAVpenetration VT-micro fuel consumption model	+26 (100% CAV) none ($\leq$50% CAV)

[*] in simulated vicinity of signalized intersections and not an entire trip gain.
[†]S: Simulation [††]E: Experimental

requires switching between maximum engine torque (pulse) and engine shut-down (glide) and could include a period of constant speed (cruise) (Ozatay et al., 2012; Wan et al., 2016). Obviously the resulting speed profile, while fuel optimal, is uncomfortable to drivers and may also be disruptive to surrounding traffic. Therefore alternative cost functions can be used that take into account passenger comfort; for instance penalizing a weighted sum of travel time and acceleration results in smoother trajectories and less braking, thus saving fuel. Optimizing for multiple lights ahead requires numerical solution methods; in (Kamalanathsharma and Rakha, 2013) and (Mahler and Vahidi, 2014), Dynamic Programming (DP) is utilized to solve the optimal control problem. In (Mahler and Vahidi, 2014) lack of deterministic information about the color of the light is handled by including probability of a green in the DP cost function and encourages vehicles to target probable green windows. Receding horizon optimization (model predictive control) has been used in (Asadi and Vahidi, 2011) and (Kamal et al., 2013) and to obtain near optimal trajectories at signalized intersections. In (He et al., 2015) the queue is considered when calculating the optimal speed. Eco departure of geared vehicles at traffic signals is discussed in (Li et al., 2015b). In (De Nunzio et al., 2017) speed advisory is proposed in conjunction with signal offsets control (green waving) for arterial bandwidth maximization and energy consumption reduction.

"Selfish" optimization that focuses on eco-driving of a single vehicle could be disruptive to the flow of following vehicles. In (HomChaudhuri et al., 2017), while still a vehicle centric optimization is solved, a more "considerate" cost function takes into account the preceding as well as the interest of the following vehicle. More specifically a "safety" term is introduced in the cost function of the host vehicle that penalizes sudden slow downs with respect to the velocity of the following vehicle.

Because this technology is unlikely to be implemented in every vehicle in the near future, it is important to evaluate the influence of equipped vehicles on other vehicles in mixed traffic flow. It is currently prohibitively difficult to do field experiments of a large number of CAVs in mixed traffic. Therefore traffic simulation tools have been used in most studies. The impact of traffic signal advisory on mixed traffic is studied, via microsimulations, in (Xia et al., 2013; Kamalanathsharma et al., 2015; Wan et al., 2016). In (Kamalanathsharma et al., 2015) and in (Xia et al., 2013) the authors evaluate the influence of eco-driving or eco-speed control on the immediate neighboring vehicles. In (Wan et al., 2016) the impact of CAVs on mixed traffic near signalized intersections is studied in traffic microsimulations. The CAVs receive the timing of signals in advance and adjust their speed for a timely arrival at green. It is shown that CAVs not only improve their energy efficiency but as their penetration increases they reduce the energy consumption of conventional vehicles as well. With the increment of CAVs, other conventional vehicles are more likely to follow a smoother moving CAV. By their simple car following strategy, such conventional vehicles may reduce the chance of stopping at intersections as well.

Potential impact on energy efficiency is summarized in Table 3.

3.3. Anticipative Car Following

Human drivers are often reactive when following other cars as their view is often blocked by the preceding car and therefore their event horizon is very limited. In sudden slowdowns, they often fail to consider the vehicles approaching from behind. This is not only disruptive to traffic flow and is unsafe, but it can result in inefficient slow-down of multiple vehicles. Balancing the position dynamically with respect to the cars in the front and back is cognitively demanding for humans. Most autonomous cars without connectivity do not necessarily do better. Many are designed to behave like human-driven vehicles and could be reactive to the perception of their immediate surrounding which results in similar short-sighted decisions. In (Mersky and Samaras, 2016) a simulation scenario depicts an automated vehicle that uses 3% more energy than a conventional vehicle baseline due to its aggressive car following strategy.

The challenge is anticipation of road events, although experienced drivers do exercise anticipation to some extent in driving (Hoogendoorn et al., 2006) (Stahl et al., 2016). We pay attention to clues and drive accordingly. For example, if we observe that a lead vehicle is accelerating and decelerating erratically we increase our following distance or change lanes. If we observe that a following vehicle is tail-gating us we try to induce a larger gap or allow that vehicle to pass. But most of these precautions are practiced in an adhoc manner, are constrained by our limited sensory and cognitive limits (Vanderbilt, 2009), and are inconsistent across different drivers (Ossen and Hoogendoorn, 2011) and traffic scenarios. These cause poor local judgments that could lead to shock waves that slow us down to inefficient crawls. Today much more can be done: thanks to better sensing capabilities, CAVs have the potential to anticipate the motion of their preceding vehicle and finely adjust their speeds for a more steady and smooth motion. Additional information of the intent of preceding vehicles via V2V communication can enhance such anticipative car following.

While the main goal should be to robustly maintain a safe following distance to the preceding vehicle (imposed as position constraints); the inter-vehicle gap can be judiciously used as a degree of freedom to filter abrupt slow-downs and application of brakes (Kamal et al., 2014) and increase energy efficiency of the host vehicle as schematically shown in Figure 4. Smoother velocity transitions of the host vehicles are expected to positively influence the motion of upstream traffic, reduce the chance of a phantom jam, caused by small disturbance, (Helbing, 2001; Sugiyama et al., 2008; Flynn et al., 2009) and lower fuel used by the entire queue of vehicles as experimentally shown in (Stern et al., 2017, 2018).

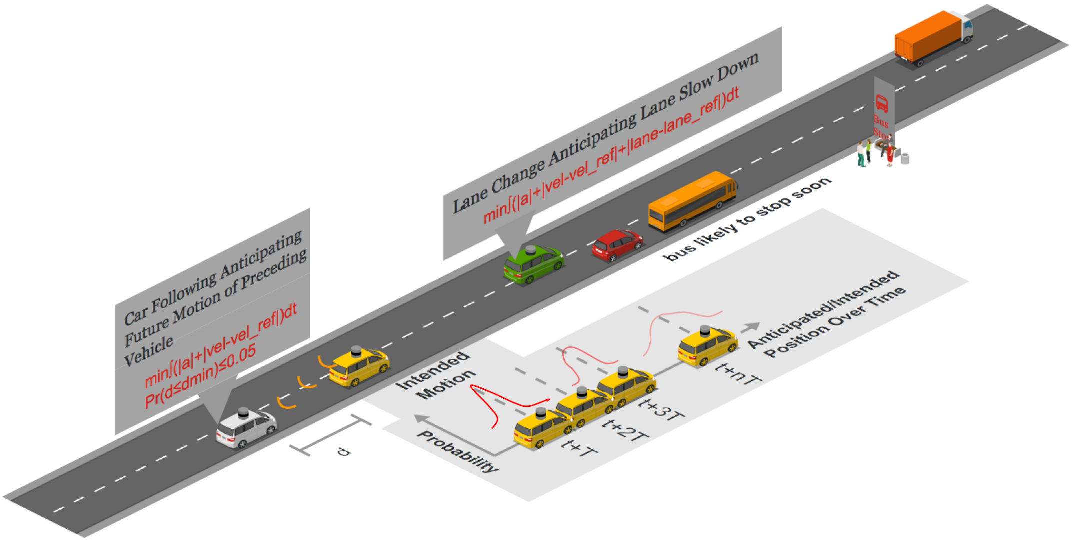

Figure 4: Anticipative car following and lane selection. The white CAV receives the imminent intentions of its preceding yellow CAV or predicts it using past statistical data and plans its motion to minimize its acceleration and velocity deviation while enforcing safe gap constraints. The green CAV which is preceded by a bus anticipates right lane traffic slow down near a bus stop and proactively starts a lane change. Its goal could be minimizing a weighted sum of its acceleration and deviations from desired velocity and lane. Most parts of the image were created on `https://icograms.com`.

Because of shorter relevant time scales in car-following, a moving horizon optimization is a natural choice (as opposed to full trip optimization). One can penalize fuel used over a moving horizon or simplify the cost function by penalizing the vehicle deceleration in order to reduce braking events. For a vehicle with a combustion engine the fuel optimal car following strategy could be pulse and glide as shown in (Sciarretta and Guzzella, 2005; Li and Peng, 2011; Li et al., 2012); but a pulse and glide strategy is uncomfortable, and could be disruptive to traffic as alluded to in (Li et al., 2015a). Therefore it may be best to penalize acceleration and deceleration or use of brakes. Safety can be guaranteed by enforcing a speed dependent lower bound on inter-vehicle gap over the horizon (Li et al., 2011). Terminal constraints can also be enforced to prevent myopic decisions (Dollar and Vahidi, 2017; Turri et al., 2017). The main challenge that arises here is dependence of the inter-vehicle constraint on the position of the preceding vehicle which is typically unknown. Therefore despite a relatively simple control problem formulation, we are faced with a difficult prediction problem.

In absence of any information and when only instantaneous velocity or acceleration of the preceding vehicle is known, the position of the preceding vehicle can be projected over the horizon assuming that it travels with constant speed (McDonough et al., 2013) or constant acceleration (Han et al., 2018). Or perhaps it is reasonable to assume that acceleration of the preceding vehicle decays over the horizon to zero with some time constant (Schepmann and Vahidi, 2011). When information from the road and infrastructure is available as discussed in Sections 3.1 and 3.2 one can construct a deterministic profile that the preceding vehicle is expected to follow.

But often the main source of uncertainty is driving style of the preceding vehicle which induces reactive transitions by the host vehicles. In this context and in the broader context of driver modeling different modeling approaches have been used. For instance (Lang et al., 2014) proposes fitting a nonlinear autoregressive model to historical data to predict the motion of preceding vehicle. In (Kamal et al., 2014) the future motion of a group of preceding vehicles is estimated via traffic microsimulations. Many have used Markov chain models to capture the statistics of velocity transitions. In essence, historical driving data from a particular driver is used to count transitions from a certain velocity (acceleration) to another and to then calculate the probability of such a transition (McDonough et al., 2011). One can then sample many potential velocity trajectories with associated probabilities and integrate them to obtain a probability distribution for the position of the preceding vehicle over a prediction horizon (Zhang and Vahidi, 2011). The inter-vehicle gap constraint can be enforced probabilistically (chance constraint) and then converted to a deterministic constraint as shown in (Zhang and Vahidi, 2011; Wan et al., 2018). Alternatively one can solve a stochastic moving horizon optimization as shown in (Bichi et al., 2010; McDonough et al., 2012, 2013, 2014; Zhou et al., 2017). For instance, in (McDonough et al., 2012) the host vehicle speed is adjusted, using stochastic Model Predictive Control (MPC), based on Markov chain predictions of traffic speed and road grade.

In an ideal scenario when all vehicles communicate, each vehicle can solve its own optimization problem and pass on its intended action to the vehicles that follow it (Dollar and Vahidi, 2017; Zheng et al., 2017). This allows a host vehicle to know, with more certainty, the position of the preceding vehicle(s) over the optimization horizon and is believed to result in smoother flow and improved overall energy efficiency. Note that in this scenario, the vehicles are just sharing intentions and do not necessarily cooperate toward a common goal. Later in section 4.1 we discuss a cooperative cruise control scenario where the vehicles could cooperate toward a "social" optimum.

With a queue of communicating vehicles, this becomes a distributed MPC problem (Zheng et al., 2017) that is solved sequentially from the front to the back of the queue. Alternatively, a centralized optimization problem can be solved on a central server for all participating vehicles and its decisions communicated to each vehicle (Besselink et al., 2016); however a central coordination scheme is complex to implement, except maybe for freight transport, and is less likely to prevail in the authors' opinion.

Table 4: Summary of selected published results on energy efficiency gain enabled by anticipative car following.

Ref.	Methods and Conditions	Efficiency gain (%)
(Manzie et al., 2007)	S[†] 1.6 ton vehicle 3 standard driving cycles for phantom lead vehicle rule-based preview car following, horizon=50 sec	+13-35 w.r.t. no preview
(Zhang and Vahidi, 2011)	S, 2 ton vehicle recorded real-data for lead vehicle winding road from Clemson, SC to Highland NC chance constrained MPC, horizon=15 sec. Markov chain prediction of lead vehicle velocity fuel economy evaluated in Argonne PSAT (ANL)	+15 w.r.t. lead vehicle
(Han et al., 2018)	S, 1.4 ton electric vehicle, no regeneration loss 3 real city driving profiles for lead vehicle MPC, horizon=100 sec Assumes constant acceleration for lead vehicle physical polynomial model for energy use	+12-44 w.r.t. lead vehicle
(Li and Peng, 2012)	S, 1.8 ton simulated vehicle with combustion engine following lead car with constant speed optimal control yields pulse and glide strategy efficiency gain is speed dependent	+0-32 w.r.t lead vehicle
(Lang et al., 2014)	E[††], engine-in-the-loop simulations, microsimulation + engine test bench measurement driver prediction: nonlinear autoregressive model prediction horizon=15 sec results depend on allowable inter-vehicle gap	+6.5-22
(McDonough et al., 2014)	E, real ego vehicle, 2007 Ford Edge 12 rounds city/highway driving on Michigan-39 following phantom vehicle with constant speed stochastic DP policy calculated offline restricted to $\pm$ 2 mph speed difference w.r.t. lead resulting strategy is pulse and glide	+3.6 w.r.t. lead vehicle
(Turri et al., 2017)	E, real ego vehicle, 3.8L V6 engine, 8 speed trans. Hyundai-Kia proving grounds, California simulated lead vehicle with sinusoidal velocity MPC tracking, perfect preview, horizon=6 sec.	+39-50 w.r.t. imperfect preview

[†]S: Simulation [††]E: Experimental

A different approach is proposed in (Kamal et al., 2014) where it is assumed that all vehicles in a queue communicate their immediate state (position, velocity, acceleration) but not their intentions. The host vehicle assumes a standard car following model for the preceding vehicles to anticipate their positions over its optimization horizon. A similar approach is discussed in (Orosz, 2016) and (Li et al., 2016). In a less than ideal scenario, when only a portion of the vehicles in a queue communicate, the position of non-communicating vehicles is inferred in (Goodall et al., 2014) at signalized intersections. Communication delay make the problem even more complex and is discussed in (Ge and Orosz, 2014; Orosz, 2016). Packet drops resulting in stochastic delays in connected cruise control and the impact on string stability are discussed in (Qin et al., 2017).

Table 4 highlights selected results that show the impact of anticipative car following on energy efficiency. As can be seen the reported gains vary significantly even for vehicles of the same size. This could be due to design and parameters of the car-following algorithms and scenario setups.

3.4. Anticipative Lane Selection and Merging

Most existing literature on eco-driving assume the vehicle maintains a single lane, reducing optimization of the vehicle motion to the choice of its velocity. In multi-lane roads, the freedom to choose a different lane provides a new dimension and many more possibilities for optimizing the motion (velocity) of the vehicle to safely improve its energy efficiency and even harmonize traffic. But every day driving experience indicates that choice of lane is a complex decision making problem, perhaps due to its combinatorial nature and typical lack of information about the average speed (or efficiency) of adjacent lanes. The same is true when merging into a highway from an on-ramp or exiting to an off-ramp. Lane selection can be a dilemma point for average drivers; aggressive lane change on the other hand can be unsafe and disruptive to the flow and efficiency of upstream traffic. Even “considerate” drivers who merge early, out of an ending lane reduce the road capacity and slow down traffic (Mele, 2016).

In a connected and automated vehicle environment, more information about the intention of neighboring vehicles can become available via V2V communication, speed of each lane could be broadcast from roadside sensors, and therefore automated vehicles can change lanes more judiciously and smoothly. See an example scenario depicted schematically in Figure 4. A rather comprehensive survey of lane change/merge for CAVs can be found in (Rios-Torres and Malikopoulos, 2017b; Bevly et al., 2016). One of the original formulations in this area can be found in (Kamal et al., 2015b, 2016) where choice of lane is an additional integer decision variable in the energy cost of the vehicle. Each CAV runs a microsimulation initialized by the current state of neighboring vehicles to determine the traffic scene over its optimization horizon. Lane and velocity of the vehicle are optimized accordingly. In (Dollar and Vahidi, 2018) the quadratic lane selection and velocity tracking cost function and the non-convex constraint set imposed by neighboring vehicles are converted to a mixed integer quadratic program and solved over a receding horizon. A hybrid optimization approach is presented in (Wang et al., 2015b). A scenario-based model predictive approach in (Schildbach and Borrelli, 2015) is intended for safe automated lane changing but also benefit energy efficiency. In (Yu et al., 2018) a game theoretic approach to automatic lane changing is proposed and is shown to outperform rule-based controllers.

Merging from ramps often causes breakdown and a phantom traffic jam in a highway. Today, solutions such as ramp metering are being used to remedy the situation (Papageorgiou and Kotsialos, 2000; Hegyi et al., 2005) which requires infrastructure investment and maintenance. With CAV technology the merge can be coordinated much more safely as experimentally shown in (Hafner et al., 2013) resulting in smoother traffic (Letter and Elefteriadou, 2017; Zhou et al., 2016) and higher energy efficiency (Rios-Torres and Malikopoulos, 2017a). The impact could go beyond individual vehicles; by reducing the chance of a phantom jam, the overall energy efficiency of traffic will improve. Table 5 summarizes the limited results that authors could find on the impact of lane selection on energy efficiency.

4. Increased Opportunities for Cooperative Driving

In a connected vehicle world, deliberate exchange of intentions by vehicles and infrastructure reduces the need for guesstimating the surrounding traffic patterns and therefore enables better coordination. Automated vehicles can cooperate rather than compete for right of way in urban areas and highways, thus contributing to harmony in motion and improved mobility and efficiency of a group of vehicles. Therefore “cooperation” in what follows, refers to sharing information and coordinating movements for a “common” good. Even with the best intentions of human drivers, cooperation among conventional vehicles is rather challenging due to often unknown plan of neighboring

Table 5: Summary of selected published results on energy efficiency gain enabled by anticipative lane selection.

Ref.	Methods and Conditions	Efficiency gain (%)
(Kamal et al., 2016)	S[†], microscopic simulations MPC velocity & lane selection, horizon=15 sec tested 2 cases, 2 km road, varying CAV levels at 50% penetration, w.r.t. conventional vehicles: at 50% penetration, w.r.t. CACC vehicles:	 +14.3(12.9)[*] +7.8(5.1)[*]
(Dollar and Vahidi, 2018)	S[†], microscopic simulations MPC velocity & lane selection converted to MIQP 4 CAVs passing slow moving vehicle in a two lane scenario 24 full-factorial simulations ordering the 4 CAVs Complete intent communication between neighboring vehicles w.r.t. a rule-based algorithm:	 +8.4
(Rios-Torres and Malikopoulos, 2017a)	S, micro-simulation in merging zone, 30 vehicles optimal coordinated merging into a highway fuel economy via polynomial metamodel in (Kamal et al., 2013) reported gain for merging period only	+48 w.r.t. yield &merge

[†]S: Simulation [*]equipped vehicles (all traffic)

vehicles and complexity of coordination at speed. For instance, merging from a ramp into a highway lacks a clear protocol and is often done in "adhoc" manner in the hope that fast approaching vehicles act with "consideration". This is not only unsafe, but the need for frequent braking in dilemma zones increases energy use and could negatively impact traffic flow. Information sharing via connectivity allows establishing more systematic coordination protocols that increase safety and efficiency. Automated vehicles can be programmed to take full advantage of such protocols that may require precise movement coordination. We describe below cooperation in car following, merging, lane changing, and intersection crossing and also discuss their potential impact on efficiency of cooperating vehicles as well as benefits to mixed traffic.

4.1. Cooperative Car Following

Cooperative car following in which vehicles coordinate in longitudinal formations is perhaps the most researched topic in cooperative driving, under the contexts of platooning and cooperative adaptive cruise control. Tight platooning gained popularity in the 1990s for its potential to increase highway throughput. In a platoon of communicating and partially automated vehicles, such as in Figure 5, the gap between a group of following vehicles can be safely reduced to increase road capacity. Moreover at short following distances, the aerodynamic drag coefficient is smaller resulting in significant energy savings, in particular for heavy duty vehicles. Recognized research programs in the USA (Browand et al., 2004; Bishop et al., 2017), Europe (Kunze et al., 2011; Alam et al., 2010; Alam, 2014), and Japan (Tsugawa, 2014) have demonstrated the feasibility of the technology in well documented road experiments as discussed in (Tsugawa et al., 2016) showing potential for 5-15% energy saving. Experimental results in (Alam et al., 2010; Alam, 2014) show between 4 to 7 percent energy saving potential for a heavy truck. Over the years, important technical challenges such as platoon string stability (Swaroop and Hedrick, 1996), communication needs (Segata et al., 2015; Willke et al., 2009), control design (Swaroop and Hedrick, 1999). (Horowitz and Varaiya, 2000), and formation scheduling (Larson et al., 2015; Luo et al., 2018) have been addressed. Today the technology has matured to the extent that major manufacturers and startup companies plan on delivering truck platooning solutions to the market in the near future with the goal of reducing energy and personnel cost (Muoio, 2017).

Over the past few years and with increased prospects for vehicle connectivity, Cooperative Adaptive Cruise Control (CACC), has gained popularity in the research community. CACC is essentially an enhanced Adaptive Cruise Control (ACC) system that, in addition to range sensor feedback, relies on wireless communication of the acceleration of the preceding vehicle(s) for feedforward control. V2V communication is intended to increase safety and allows string-stable reduction of the inter-vehicle gap for improved road utilization (Naus et al., 2010). With a correct design, velocity variations are much better attenuated than in ACC car following, as shown in road experiments with six equipped vehicles in (Ploeg et al., 2011). Experimental results in (Milanés et al., 2014) showed string stable

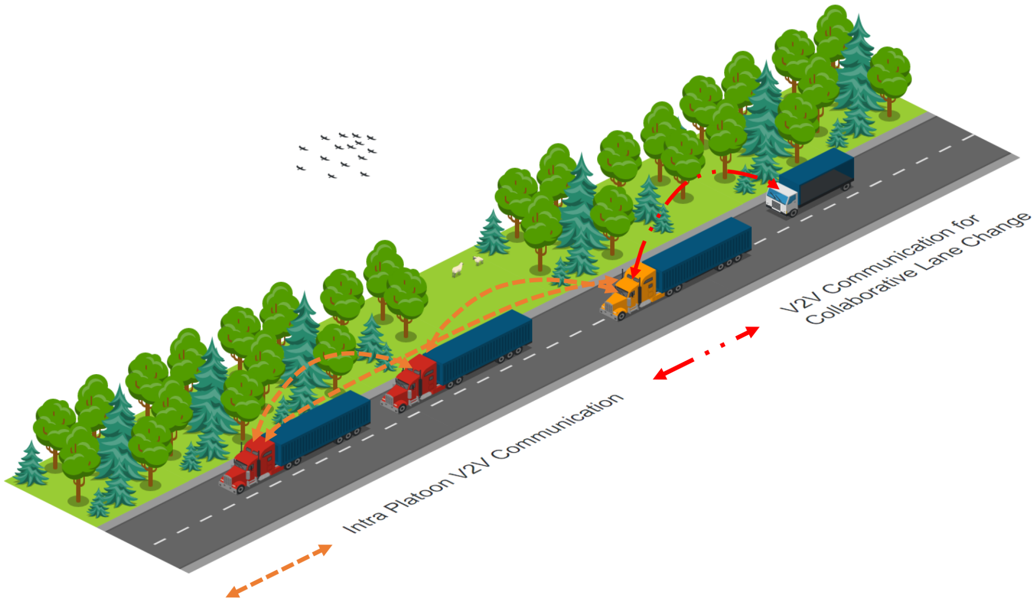

Figure 5: Collaborative car following and lane selection. The red trucks maintain a platoon formation relying on V2V communication and automated longitudinal control. The yellow truck communicates with the red trucks to join the platoon. In a collaborative lane change maneuver enabled by V2V communication, the white smaller truck leaves a gap for the yellow truck to change lane. Most parts of the image were created on `https://icograms.com`.

operation of a CACC design at a short time headway of 0.6 seconds in scenarios where a production ACC design failed to maintain stability even though it was operating at larger 1.1 second headway. The 2011 Driving Challenge in Netherlands was a successful showcase of CACC technology by multiple teams. An overview of this competition is presented in (Ploeg et al., 2012; Van Nunen et al., 2012) and the details of each team's technical contribution is well documented in separate papers (Geiger et al., 2012; Lidström et al., 2012; Kianfar et al., 2012; Mårtensson et al., 2012; Nieuwenhuijze et al., 2012; Guvenc et al., 2012). CACC formations could positively or negatively impact surrounding traffic as demonstrated in a simulation study (Van Arem et al., 2006), for instance long formations may prevent those that intend to merge into a highway. But overall, CACC is expected to have a harmonizing impact on participating vehicles and on surrounding traffic, reducing braking events and lowering energy consumption. Despite these benefits there are few papers documenting the energy efficiency impact of CACC, for instance (Lang et al., 2014). It appears that reducing energy efficiency has been mostly the focus of truck platooning projects.

While the platoon and CACC terminologies are sometimes interchangeably used in the literature, there are some differentiating features. The original concept of a platoon relied on a designated lead vehicle and a hierarchical control structure from the lead to the following vehicles. This hierarchy is not needed in CACC car following and each vehicle can individually switch to its CACC mode as long as it receives messages communicated by its preceding vehicles. The information flow between vehicles can vary from one implementation to the other. A vehicle can receive information from the lead vehicle only, from its preceding vehicle only, or from multiple preceding vehicle as schematically shown in (Orosz, 2016) and (Zheng et al., 2014). Depending on the information flow and content shared between vehicles, we can envision enhanced versions of current platooning and CACC practices. Ideally each vehicle will share its intended acceleration profile over a future horizon, rather than its instant acceleration, with all its following vehicles (Dollar and Vahidi, 2017; Zheng et al., 2017). This reduces the uncertainty about the movement of preceding vehicles as was discussed in Section 3.3 aiding each vehicle to better plan its motion and reduce braking events. Note that in this scenario, cooperation is only via information sharing, and each vehicle optimizes its "selfish" cost function. In a true collaborative environment, a group of CAVs not only share information but look for the "social optimum" by optimizing a common cost function (Zheng et al., 2017) or by formation consensus rules (Di Bernardo et al., 2015). The common goal for instance could be reducing the fuel consumption of the entire fleet (Besselink et al., 2016; Lelouvier et al., 2017; HomChaudhuri et al., 2017), string stability (Dunbar and Caveney, 2012), or collision mitigation (Wang et al., 2015a). A common cost can still be optimized in a distributed fashion onboard each vehicle based on information communicated by neighboring vehicles to reach a consensus (Dunbar and Caveney, 2012; Lelouvier et al., 2017). In a centralized control framework described in(Lelouvier et al., 2017), the common fuel cost is optimized on a central cloud server for a group of freight trucks and the decision is issued to low-level controllers of individual trucks. Table 6 summarizes some of the limited results on energy efficiency impact of cooperative car following, including platooning.

Table 6: Summary of selected published results on energy efficiency gain enabled by cooperative car following.

Ref.	Methods and Conditions	Efficiency gain (%)
(Lelouvier et al., 2017)	S†, group of five 1.2 ton electric vehicles eco-platooning for reduced group consumption considered drag reduction nonlinear MPC, prediction horizon=120 sec studied centralized and distributed solutions	+10.5
(Dollar and Vahidi, 2017)	S, microsimulation, combustion engine vehicles 10 CAVs follow lead vehicle, share partial info drag reduction is not considered each CAV solves MPC, horizon=12 to 20 sec fuel use evaluated using an engine map compared against IDM car following	+50 for FTP cycle following
(Browand et al., 2004)	E††, truck platooning 2.4 km unused runway, Crows Landing two identical Freightliner tractors, 16 m trailers 90 km/h constant speed, 3-10 meter spacing	+8-11
(Alam, 2014)	E, truck platooning, 45 km Swedish highway Three 18 m, 37-39 ton Scania tractor-trailers wirelessly communicate vel., accel., parameters time headway=1 second	+4-6.5
(Tsugawa, 2014)	E, truck platooning on a test track 3 fully-automated 25 ton trucks & 1 light truck communicate vel,, accel., brake via DSRC 80 km/h constant speed, 4.7 meter gap	+15
(Bishop et al., 2017)	E, truck platooning on test track 2 Peterbilt tractors, full aerodynamic packages 16 m trailers weighing 30 ton high-speed oval track, banked turns 105 km/h and 10 m following distance	+7.0

†S: Simulation ††E: Experimental

4.2. Cooperative Lane Change and Merge

In Section 3.4 we discussed that individual CAVs can benefit from connectivity and autonomy and more safely and efficiently merge and change lanes. Additional gains are expected if CAVs cooperate, not only by sharing intentions but also by being "considerate" of neighboring vehicles as shown schematically in Figure 5. In such a cooperative scenario, each vehicle includes in its objective function, the impact of its decision on neighboring vehicles. Lane change and merge decisions can then be made in a distributed manner with each vehicle deciding (optimizing) its motion and sharing its intentions (Nie et al., 2016). Alternatively, in a centralized framework, a single decision-making (optimization) problem is solved for a group of cooperative vehicles (Cao et al., 2015). Cooperative lane selection and merge not only contributes to efficiency of the cooperating fleet but can also have a positive harmonizing effect on surrounding traffic.

There is a large body of literature on lane change models for traffic microsimulations, such as the widely used MOBIL lane change model introduced in (Kesting et al., 2007). However cooperative lane selection and merging for CAVs has only been recently discussed. In (Awal et al., 2015) a cooperative lane-changing algorithm is simulated that considers follower vehicles in current and target lanes when making a lane change decision. In (Scarinci et al., 2017) a cooperative merging assistant is introduced to facilitate merging on ramp traffic and relying on vehicle connectivity. The simulations in (Awal et al., 2015) show improvement with respect to MOBIL, in terms of merge time and rate, wait time, fuel consumption, average velocity, and flow at the cost of slightly increased travel time for main road vehicles. In (Scarinci et al., 2015) a merging assistant system that relies on vehicle cooperation, reduces the number of "late-merging" vehicles and subsequent likelihood of flow break-downs. Different algorithms for cooperative merging have been proposed, for instance (Mosebach et al., 2016) proposes a decentralized control method and (Cao et al., 2015) formulates it in a model predictive control framework. A cooperative V2V "negotiation" process for lane changing is described in (Lombard et al., 2017) and (Kazerooni and Ploeg, 2015) proposes interaction protocols for cooperative lane changing. A game theoretic perspective for cooperative lane changing is simulated in (Zimmermann et al., 2018) for CAVs and incentives for cooperation are discussed. Experiments with 3 CAVs performing a semi-automated cooperative lane change maneuver are described in(Raboy et al., 2017) and show the potential for smoother velocity trajectories. The focus of the above results has not been energy efficiency and only (Awal et al., 2015) reports energy efficiency gains. However, we expect considerable energy saving from wide deployment of cooperative lane changing and merging system due to reduced braking events and harmonizing effect on traffic flow.

4.3. Cooperative Intersection Control

The coordination and optimal timing of traffic signals are by nature complex problems and backed by years of research in traffic engineering and operations research. Current signal timings are mostly scheduled offline, the optimized timings are then deployed as fix timetables for different times of the day. Many signals are actuated by traffic and have rules to override their pre-optimized timetables based on the state of their loop-detectors to reduce idling at intersections. While these traffic responsive control strategies calculate their timing in real-time (Diakaki et al., 2002), they act based on the immediate state of loop-detectors. On the other hand, smart traffic signal controllers in connected vehicle environments will do more than just signaling right of ways and act intelligently as hubs that sense, route, and harmonize the flow of arterial traffic. The research on uni-directional signal to vehicle communication for improving efficiency by providing speed advisory to individual vehicles was discussed in Section 3.2. Another research direction has focused on improving intersection flow by optimizing timing of traditional traffic signals informed by uni-directional communication from connected vehicles (He et al., 2012; Kamal et al., 2015a). In addition, bi-directional vehicle-signal communication allows the geographical data of the connected vehicles to be also wirelessly transmitted in real-time to smart traffic signal controllers (Goodall et al., 2013). This increases energy efficiency and intersection flow as signals adjust their timings and vehicles their speeds (De Nunzio et al., 2017).

Automated vehicles can further benefit from the communicated traffic signal information because they not only process the incoming information rather effortlessly but also can precisely control their speed and arrival time at a green light. The situation can get even better with 100% penetration of automated vehicles since a physical traffic light is not needed anymore as shown in concept papers by (Dresner and Stone, 2008; Ferreira et al., 2010; Ferreira and d'Orey, 2012). Also because automated cars have much faster reaction times than human driven vehicles, the intersection controller can rapidly switch between phases (Guler et al., 2014). Some of the benefits of eliminating traffic signals in an all automated vehicle environment is discussed in (Dresner and Stone, 2008) and demonstrated by interesting simulation results in a recent publication (Tachet et al., 2016). In (Huang et al., 2012) the potential for 50% energy efficiency gain via such reservation-based intersection control systems is shown. In (Fayazi et al., 2017) increasing the intersection throughput is formalized as an Mixed Integer Linear Programming optimization problem. They show significant reduction in number of stops and fuel use compared to traditional intersection control schemes. In a one hour microsimulation case study it is shown that the number of stops can be reduced 100 times (Fayazi and Vahidi, 2018). Via a vehicle-in-the-loop experiment (Fayazi and Vahidi, 2017) they measure 20 % improvement in energy efficiency of a real-vehicle that interacts with the intersection controller and hundreds of simulated vehicles. The proposed MILP-based controller resides on a computational server and creates a live picture of evolving traffic conditions by tracking all subscribing vehicles. Based on the location and speed of all the vehicles, the controller optimally and regularly schedules the intersection access time for each vehicle. In addition to minimizing intersection delay and ensuring intersection safety, the desired arrival time of the vehicles is incorporated into the optimization problem in such a way that vehicles would not face extreme delay or expedition compared to their desired arrival times. In (Ashtiani et al., 2018) the concept is extended to multiple intersections. Simulations indicate benefits of such systems greatly increase if vehicles move in platoons, in certain cases doubling the arterial network capacity with the coordination of platoons and intersections (Lioris et al., 2015). In (Jin et al., 2013) a platoon-based approach

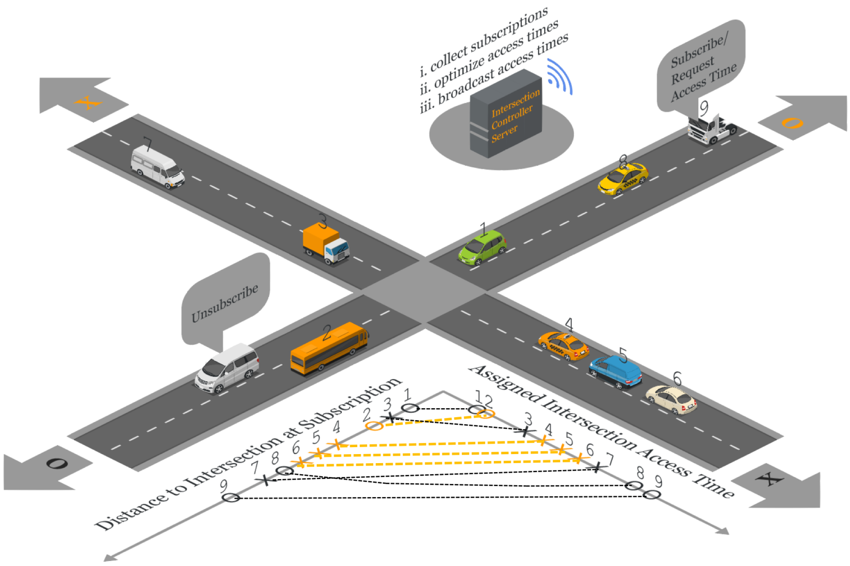

Figure 6: Schematic of a cooperative intersection. CAVs subscribe to an intersection control server as they approach the intersection, the controller assigns access times to each approaching vehicle allowing only vehicles of the same movement in the intersection area at the same time. In this schematic vehicles on movements X and O are grouped together when assigning acces times which reduces idling and saves energy. Most parts of the image were created on `https://icograms.com`.

shows up to 20% energy efficiency benefit with respect to signalized intersections, but under simulation conditions of (Jin et al., 2013) energy efficiency was a little sacrificed to form platoons. Table 7 highlights some of the key results on energy benefits of cooperative intersection control.

4.4. Indirect Benefits Through Traffic Harmonization

Coordinated and smoother motion of CAVs could harmonize the surrounding traffic and contribute to energy efficiency of conventional vehicles, even at low penetration levels. While it is difficult to establish the network wide benefits experimentally, there are microsimulation case studies and isolated experiments that show such positive impacts. For instance in Section 3.2 we explained that according to (Wan et al., 2016) traffic signal speed advisory can reduce the energy consumption of conventional vehicles at moderate penetration rates. Several papers have shown the harmonizing effect of automated cruise control on the upstream traffic (Kamal et al., 2014; Koshizen et al., 2015) which is expected to positively influence energy efficiency of upstream traffic. CACC not only increases road utilization due to smaller gaps (Van Arem et al., 2006; Naus et al., 2010; Shladover et al., 2012), but is shown to attenuate velocity variations as shown in road experiments in (Ploeg et al., 2011; Milanés et al., 2014). These findings are corroborated by microsimulation studies, reported in (Talebpour and Mahmassani, 2016), that show reduction of shock waves with increased penetration of connected and automated vehicles. In (Nishi et al., 2013) a “theory for jam-absorption driving” is presented which is a method for driving a single car to attenuate a traffic shockwave, followed by experiments in (Taniguchi et al., 2015). An interesting experiment with a group of 22 vehicles moving on circle, showed that a single automated vehicle using relatively simple control rules, could dissipates the phantom jam waves formed by the 21 human driven vehicles. This contributed to between 20 and 40 % improvement in average fuel economy of the fleet across the 3 experiments as measured using each vehicle’s OBD-II port (Stern et al., 2017, 2018). Harmonizing impact of CAVs in an open highway is demonstrated via interesting experiments in (Ma et al., 2016). Three CAVs were driven side-by-side in real shock-wave traffic near Washington DC and their influence was measured by three probe vehicles that were deployed downstream and upstream. It was observed that CAVs reduced the oscillation induced by the shock-waves and harmonized the traffic and is expected to have network-wide energy efficiency impact. Secondary effects due to reduced number of accidents, could further lower delays and loss of energy which is difficult to quantify.

Table 7: Summary of selected published results on energy efficiency gain enabled by cooperative intersection control.

Ref.	Methods and Conditions	Efficiency gain (%)
(Huang et al., 2012)	S[†], microsiumlations in Paramics (Paramics, 2009) real-world road network, 3 intersections CMEM (Scora and Barth, 2006) fuel efficiency evaluation	+50%
(Jin et al., 2013)	S, microsimulation in Sumo 1 intersection with 2 single lane approaches vehicles form platoons to pass intersection CMEM fuel efficiency evaluation	+11-21
(Ferreira and d'Orey, 2012)	S, Microsimulation in DIVERT (Fernandes et al., 2010) simulated entire network of Porto, Portugal EMIT (Cappiello et al., 2002) fuel consumption and emission model 1.3 ton combustion engine vehicle mostly studied emissions reduction	+25 (fuel) +1-18 (CO_2 emissions)
(Fayazi and Vahidi, 2017)	E[††], real vehicle interacting with microsimulation real vehicle: 2011 Honda Accord 2.4 L engine custom microsimulation written in JAVA 12 laps, 1.6 km track, single virtual intersection scheduling via Mixed Integer Linear Programming	+20 for real vehicle

[†]S: Simulation [††]E: Experimental

5. Conclusions

This paper presented an overview of energy-efficient driving opportunities provided by connected and automated vehicles through first-principle analysis and a survey of eco-driving literature. Unprecedented access to information via advanced sensors and V2X communication, increased processing power, and precision positioning and control, enables connected and automated vehicles to plan and execute eco-driving maneuvers much better than a human driver. While there are limited previous studies on energy impact of CAVs, review of the eco-driving literature promises considerable benefits. In particular our conservative evaluation based on published *experimental* results indicates 3% energy saving from preview of static road information such as road grade in highway driving. Information from traffic signals via V2I, could lead to 10% energy saving in arterial driving. With full penetration of CAVs reservation based intersections could yield up to 20% savings. Anticipative car following has a more uncertain impact but could at least yield 3% gain or much higher depending on the driving scenario. Platooning for trucks could yield 7-10% gain due to drag reduction. Cooperative car following and lane selection for passenger cars could boost energy efficiency but there is a lack of experimental results to report. And the harmonizing impact of CAVs on traffic, even at low penetration levels, could result in 20% savings in stop and go driving.

Most of the benefits can be achieved without additional hardware costs and relying mainly on software and information. Higher energy efficiency is an attractive added feature of CAVs, beyond safety and comfort, that could accelerate their market adoption. With higher penetration, there will be system wide influences by such "eco-CAV"s, potentially lowering global energy use and contributing positively to the environment. Energy efficient driving of CAVs could be encouraged by proactive policy making countering alternative scenarios in which higher CAV-miles traveled at higher speeds increase global energy use.

Appendix

We want to find the velocity profile that minimizes the "wheel-to-distance" energy losses, going from velocity of v_0 to v_f over a specified time of t_f and distance of s_f.
Here we break down the wheel force F_w to tractive force F_t and braking force F_b. Considering the tractive acceleration, $u_t = \frac{F_t}{m}$, and braking deceleration $u_b = \frac{F_b}{m}$ as the two inputs, and choosing position as the independent variable, the

equations of motion can be written in the following state-space form:

$$\begin{cases} \dfrac{dt}{ds} = \dfrac{1}{v} \\ \dfrac{dv}{ds} = \dfrac{u_t - u_b - \beta v^2 - h(s)}{v} \end{cases} \tag{5}$$

where $\beta = \frac{1}{m}0.5\rho_a A C_D$ and $h(s) = g(sin\theta + C_{rr}cos\theta)$. The boundary conditions are:

$$v(s_0) = v_0, \quad v(s_f) = v_f, \quad t(s_0) = 0, \quad t(s_f) = t_f$$

To keep the derivation applicable across a wide range of vehicles, we assume that a fraction η of the braking energy can be recuperated ($\eta = 0$ for conventional vehicles and $\eta = 1$ for vehicles with ideal regeneration). Therefore to optimize the "wheel-to-distance" energy expenditure, we minimize the following cost function, which is energy spent normalized by vehicle mass:

$$\min_{u_t, u_b} J = \int_0^{s_f} (u_t - \eta u_b) ds \tag{6}$$

subject to the equations of motion and their imposed boundary conditions. It is assumed that there are no bounds on the states over the control interval but $0 \leqslant u_t \leqslant \bar{u}_t$ and $0 \leqslant u_b \leqslant \bar{u}_b$. Replacing for u_t from Equation (5), we obtain:

$$J = \frac{1}{2}(v_f^2 - v_0^2) + \int_0^{s_f} h(s)ds + \int_0^{s_f} (\beta v^2 + (1-\eta)u_b)ds \tag{7}$$

The first two terms do not depend on the control input. Therefore we solve the following problem:

$$\min_{u_t, u_b} \int_0^{s_f} (\beta v^2 + \gamma u_b) ds \tag{8}$$

where $\gamma = 1 - \eta$, so in absence of regeneration $\gamma = 1$.

Following Pontryagin's Minimum Principle (Kirk, 2012), the Hamiltonian $\mathcal{H}$ is formed as follows:

$$\mathcal{H} = \beta v^2 + \gamma u_b + \lambda \frac{1}{v} + \mu \frac{u_t - u_b - \beta v^2 - h(s)}{v} \tag{9}$$

where λ and μ are the costates with the following dynamics:

$$\begin{cases} \dfrac{d\lambda}{ds} = -\dfrac{\partial \mathcal{H}}{\partial t} = 0 \Rightarrow \lambda = constant \\ \dfrac{d\mu}{ds} = -\dfrac{\partial \mathcal{H}}{\partial v} = -2\beta v + \lambda \dfrac{1}{v^2} + \mu \dfrac{u_t - u_b - h(s)}{v^2} + \beta \mu \end{cases} \tag{10}$$

where boundary conditions for both λ and μ are free, since both states, t and v, are fixed at initial and final positions. We also note that λ is a constant over position, since its rate of change is zero while dynamics of μ is more complex. The optimal inputs should minimize the Hamiltonian. Since $\mathcal{H}$ is an affine function of u_t and u_b and therefore

$$\frac{\partial \mathcal{H}}{\partial u_t} = \frac{\mu}{v}, \quad \frac{\partial \mathcal{H}}{\partial u_b} = \gamma - \frac{\mu}{v}$$

are independent of the inputs, the Hamiltonian is minimized at extreme values of the inputs, except for when the partial derivative of $\mathcal{H}$ with respect to the inputs is zero, in which a so-called singular interval may exist. Over a singular interval the inputs could assume a value within their constraints. The optimal traction force, denoted by u_t^* is:

$$u_t^* = \begin{cases} \bar{u}_t & \mu/v < 0 \\ u_t^s & \mu/v = 0 \\ 0 & \mu/v > 0 \end{cases} \tag{11}$$

where u_t^s denotes the wheel traction during a possible singular interval. For a singular interval to exist, the condition $\frac{\mu}{v} = 0$ must be valid for a position interval rather than just at one point. Therefore over a singular interval we must have

$$\frac{d}{ds}\left(\frac{\mu}{v}\right) = \frac{1}{v}\frac{d\mu}{ds} - \frac{\mu}{v^2}\frac{dv}{ds} = 0 \tag{12}$$

upon substitution from (5) and (10), the condition for existence of a singular interval simplifies to:

$$\frac{d}{ds}\left(\frac{\mu}{v}\right) = -2\beta + \frac{\lambda}{v^3} + \beta\frac{\mu}{v} = 0 \tag{13}$$

but since on a singular interval during traction $\frac{\mu}{v} = 0$, we conclude:

$$v_s = \left(\frac{\lambda}{2\beta}\right)^{\frac{1}{3}} \tag{14}$$

which is a constant since optimal λ was shown to be a constant. As a result the traction force is $u_t^s = \beta v_s^2 + h(s)$. The optimal braking force, denoted by u_b^* is:

$$u_b^* = \begin{cases} 0 & \mu/v < \gamma \\ \bar{u}_b & \mu/v > \gamma \end{cases} \tag{15}$$

In other words there is no singular interval during braking: For a singular interval to exist during braking, the condition $\frac{\mu}{v} = \gamma$ must be valid for a position interval rather than just at one point. Equation (13) indicates that during a braking singular interval the velocity has to be a constant. But we know that during braking the velocity cannot remain constant, hence there is no singular interval during a braking phase.

In summary Eq. (11) states that to minimize "wheel-to-distance" energy expenditure, the vehicle should decelerate or accelerate, as quickly as possible, to the constant speed of v_{sing} and maintain that speed till close to destination. Optimal deceleration strategy starts by coasting but could end with a period of maximal braking even in absence of regeneration ($\gamma = 1$). With ideal regenerative brakes ($\gamma = 0$) the optimal strategy does not include a coasting phase. Values of v_{sing} and λ will be smaller for longer trip times t_f; its value can be obtained after solving the two-point boundary value problem described by (5) and (10).

ACKNOWLEDGMENT

The first author was a scientific visitor at IFP Energies Nouvelles, Rueil-Malmaison, France May-August 2017 during which this paper was written. He thankfully acknowledges the support and sponsorship provided by IFPEN. The authors thank, Dr. Jihun Han, for his suggestions on the organization of the paper.

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